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# Beyond Human Error: How Road Design and Urban Environmental Factors Drive Major Accidents in Jakarta

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***Abstract***. *Jakarta, Indonesia's capital and a major megacity, faces significant road safety challenges due to its dense population, high mobility, and complex urban environment. While human error is often cited as the primary cause of traffic accidents, growing evidence suggests that environmental factors—such as road design, land use, and weather conditions—also play a critical role. This study examines the influence of these factors on major road accidents, defined as those resulting in serious injuries or fatalities, in Jakarta from 2019 to 2023. Using a binary logistic regression model and a dataset of over 19,000 accidents across 4,654 road segments, this research identifies key predictors of accident severity. The findings reveal that weekends, peak traffic hours, adverse weather, and specific road types (e.g., one-way four-lane roads) significantly increase the likelihood of major accidents. Furthermore, industrial land use emerges as a high-risk factor, while government and public service zones are associated with reduced accident risks. These results highlight the urgent need to integrate environmental factors into urban road safety strategies. The study offers actionable insights for policymakers and urban planners, including recommendations for road design improvements, better land use planning, and targeted traffic enforcement. While focused on Jakarta, the findings provide valuable lessons for other rapidly urbanising cities worldwide, particularly in developing regions where similar challenges persist.*

***Keywords***. *Road safety, major traffic accidents, environmental factors, Jakarta.*

## Introduction

Road traffic accidents remain a leading cause of death and disability worldwide, with an estimated 1.19 million fatalities each year; road traffic injuries are the leading killer of children and young people aged 5-29, and nine in ten of these deaths occur in low- and middle-income countries (LMICs) (WHO, 2023). The economic burden is comparably severe: road injuries are projected to cost the global economy US$1.8 trillion between 2015 and 2030 (Wang et al., 2022; Chen et al., 2019). These costs fall disproportionately on densely populated, rapidly motorising urban areas, where high mobility and mixed traffic make accidents both frequent and severe.

Road safety research has long been dominated by a paradigm that attributes the majority of crashes to human error. In this view, driver behaviour and vehicle condition are the principal determinants of accident occurrence and severity (O'Donnell and Connor, 1996; Mannering et al., 2016), and modifying road user behaviour is therefore the primary lever for improving safety. This paradigm is not without empirical support: behavioural factors such as speed, distraction, and impairment are proximate causes in a large share of collisions, and a combination of

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behavioural, legislative, and infrastructural measures has contributed to documented declines in road deaths in many countries (WHO, 2023). Yet the persistence of this attribution also reflects how crash data are produced and how responsibility is assigned. Police crash reports, the most widely used source of accident statistics, categorise contributory factors predominantly around the road user, and this category structure is subject to well-documented reporting biases (Rolison, 2020). Legal frameworks compound the bias, as liability systems search for a blameworthy party, directing causation analysis toward the driver and away from the designers, operators, and regulators of the road system (Lie and Tingvall, 2023). Attribution to human error is therefore partly an artefact of the data and legal lenses through which crashes are observed, not simply a neutral finding of the evidence.

The conceptual foundations of the paradigm are equally fragile, because the distinction between human and environmental causes dissolves once road design is recognised as a determinant of driver behaviour. Self-explaining road principles hold that the road environment should be designed to elicit safe behaviour, and that ambiguous or inconsistent design invites the very errors that are later attributed to drivers (Theeuwes, 2021). The safe system approach formalises this insight: it takes human fallibility as its starting premise and requires that roads, speeds, and vehicles be designed to be forgiving of mistakes (Larsson and Tingvall, 2013). A substantial empirical literature is consistent with this view, showing that road width, geometry, and functional classification are associated with accident rates (Hashimoto et al., 2016), that geometric design inconsistency degrades safety beyond the effect of design features alone (Ng and Sayed, 2004), that traffic density in urban settings raises accident risk and severity (Retallack and Ostendorf, 2020), and that adverse weather impairs visibility, braking, and vehicle handling (Li et al., 2019). The debate, therefore, is not whether human error matters, but whether major road traffic accidents should be understood primarily as failures of individual road users or as outcomes emerging from interactions between human behaviour and the systems in which that behaviour occurs. From the latter perspective, risky behaviour may not be an isolated cause but partly a response to, or interaction with, road design, traffic conditions, land use, and other environmental constraints. The critical empirical question is consequently not simply whether drivers make errors, but whether the physical and spatial environments in which those errors occur systematically influence the severity of major accidents. This question remains insufficiently examined in many urban contexts, particularly in rapidly developing cities of the Global South where heterogeneous road environments and intense mobility create distinctive conditions for road-user interaction.

Evidence capable of answering this question remains scarce, particularly for low- and middle-income countries, where the gaps are geographical, conceptual, and empirical at once. Geographically, quantitative evidence on environmental determinants of accident severity is concentrated in high-income countries, where traffic composition, infrastructure standards, and enforcement capacity differ fundamentally from LMIC conditions (Heydari et al., 2019); whether relationships estimated there transfer is assumed, not demonstrated, a problem made more acute by the fact that the design principles of the safe system approach remain largely absent from infrastructure development in most LMICs (Godthelp, 2023). Conceptually, environmental variables are typically included in severity models as control covariates rather than as a primary explanatory framework, so their independent contribution to accident severity is rarely quantified on its own terms. Empirically, the Indonesian evidence base is limited to macro-level descriptions of accident patterns (Jusuf et al., 2017; Soehodho, 2017) and analyses of specific user groups, such as pedestrian crashes in Jakarta and its satellite cities (Siregar et al., 2019); no study has yet modelled how road design, land use, weather, and temporal factors jointly predict the severity of major accidents across Jakarta's urban network, nor has any tested whether environmental relationships established elsewhere hold in a motorcycle-dominated city, such as Jakarta. Data constraints compound these gaps: accident records in LMICs suffer from under-reporting and rarely include the spatial attributes required to link crashes to their environment (Heydari et al., 2019). The result is that environmental determinants remain systematically under-observed in precisely the settings—rapidly urbanising cities of the Global South—where they may matter most.

Jakarta, Indonesia's largest metropolitan area, is a setting in which these environmental risk factors converge. With over 10 million residents in the city proper and more than 30 million in Greater Jakarta, the city experiences intense daily commuting across private vehicles, motorcycles, public transport, and informal modes. Motorcycle-dominated traffic, which accounts for the majority of accidents and fatalities in Indonesia, shares corridors with cars and buses in facilities that are often poorly segregated (Jusuf et al., 2017; Soehodho, 2017). Mixed land use that interweaves residential, commercial, and industrial zones concentrates vehicle-pedestrian conflicts and freight movement in the same corridors (Kaygisiz et al., 2017). Seasonal flooding during the rainy season degrades road surfaces, reduces visibility, and creates slippery conditions (Ashley et al., 2015), while ongoing construction introduces temporary hazards. Weak enforcement compounds these conditions by permitting speeding, poor lane discipline, and signal violations (Tamakloe et al., 2021). Within such an environment, attributing crashes to driver error alone is difficult to sustain: many of the errors observed on Jakarta's roads occur where the infrastructure provides ambiguous cues, mixed speeds, and little protection against the consequences of a mistake.

Jakarta offers an analytically valuable setting for addressing these gaps. As a megacity where the environmental risk factors described above converge, it functions as a critical case: if environmental predictors of severity can be identified even where behavioural attribution is the institutional default and data are imperfect, the case for treating the built environment as a first-order determinant is strengthened rather than weakened. Jakarta is also a representative case: its combination of motorcycle-dominated traffic, severe congestion, and mixed land use is shared, in varying degrees, by other Southeast Asian megacities, so evidence generated here speaks to a broader class of rapidly urbanising contexts rather than to a single city. The study exploits the natural variation in these conditions, including seasonal weather extremes and marked heterogeneity in road design and land use across districts, to estimate the marginal contribution of environmental factors to the severity of major road accidents in Jakarta between 2019 and 2023 using binary logistic regression. In doing so, it tests, rather than assumes, the transferability of relationships established in high-income settings. The study contributes in three ways. Empirically, it provides the first systematic, city-wide assessment of how road design, land use, weather, and temporal factors predict the severity of major accidents in Jakarta. Theoretically, it interrogates the human-error paradigm by estimating how much of the observed variation in severity is associated with environmental conditions when those conditions are modelled explicitly. Practically, it identifies modifiable environmental factors that can be targeted through road design and traffic management, providing an evidence base for interventions that complement, rather than replace, enforcement-based approaches.

The remainder of this paper is organised as follows. Section 2 reviews the literature on environmental determinants of traffic accidents and introduces the variables examined in this study. Section 3 describes the data and the binary logistic regression approach used to model the severity of major accidents. Section 4 presents the estimation results and discusses the influence of each environmental factor, covering temporal patterns, weather, road design, and land use. Section 5 concludes with the main findings, their implications for road safety policy and urban planning, and the limitations that point to directions for future research.

## Literature Review

A traffic accident is an unexpected event that occurs on the road, involving vehicles and other road users or the vehicle itself, which can result in damage and/or injury. The phenomenon of traffic accidents is a complex event that often involves various interacting and dynamic factors within the transportation context. These factors include human behaviour, vehicle conditions, and environmental influences, all of which can contribute to the unpredictability and severity of such incidents (K. Wang et al., 2022). Several studies have revealed that human behavioural factors, such as negligent driving, lack of concentration, traffic violations, and substance abuse, are among the dominant factors that can trigger adverse incidents on the road (O'Donnell and Connor, 1996; Washington et al., 1999). In addition to human factors, vehicle conditions also influence the risk of traffic accidents. In the study by Komačková and Poliak (2016), it is mentioned that vehicle factors can affect traffic safety through two aspects: design and performance. Tang et al. (2018) also reinforce that the condition and performance of vehicles play a crucial role in the risk of traffic accidents. Furthermore, environmental factors play a crucial role in determining the incidence and severity of traffic accidents, which can ultimately result in fatalities. As one of the significant contributing factors, the role of the environment in traffic accidents deserves in-depth examination. In the context of traffic accidents, environmental factors include infrastructure, weather conditions, and the surroundings of road segments.

As a fundamental element of the transportation system, road infrastructure encompasses various factors such as road design, surface condition, traffic signals, lighting, and more. A study conducted in Japan, exploring the relationship between traffic accidents and urban characteristics, including road infrastructure factors, found that road design within the width categories of 3 – 5.5 metres and 5.5 – 13 metres significantly influences the factors contributing to accidents in several models, with a p-value of less than 0.01 (Hashimoto et al., 2016). On the other hand, the width of a road has a varied impact on the severity of injuries resulting from accidents (Zeng et al., 2017). However, different results were observed in a study conducted in Novi Sad, Serbia, where the findings indicated that road design, specifically road length, had a significantly negative impact on the factors influencing the occurrence of accidents in that city, with a confidence level of 90% (Pljakić et al., 2022). These findings highlight the complexity of the influence of road infrastructure on traffic safety, which is further affected by various contextual factors unique to each location. This underscores the critical importance of road infrastructure in promoting traffic safety and reducing both the incidence and severity of accidents in urban areas.

In addition to road infrastructure, road characteristics such as traffic density and vehicle speed also contribute to the occurrence of traffic accidents. Several studies conducted to understand the impact of traffic density on traffic accidents have indicated that traffic volume has a significantly positive influence on the occurrence of accidents (Retallack and Ostendorf, 2020; Saadat et al., 2019). Furthermore, studies conducted by Saadat et al. (2019) in Tehran, Wier et al. (2009) in San Francisco, and Mannering et al. (2016) in Florida concluded that traffic accident rates and the severity of traffic accidents, which can result in fatalities, are also influenced by traffic density.

Based on previous studies, various environmental factors have been identified to examine their impact on traffic accidents in different study areas. Table 1 summarises the environmental factors that have been identified by previous research, providing an overview of determining the variables to be identified in this study. The environmental variables analysed in this study include ten key aspects. First, the day of the accident is categorised into weekdays and weekends. Second, the time of the accident is grouped into morning peak hours and afternoon peak hours. Third, weather conditions are classified as good weather or bad weather. Fourth, road function is divided into four categories, ranging from toll roads to local roads. Fifth, road classification is grouped into three classes. Sixth, road type is categorised based on the number of lanes and the presence of road dividers. Seventh, road geometry includes 11 shapes, from straight roads to various intersections, such as T-intersections. Eighth, road width is classified into nine types. Ninth, land use around the road is divided into eight categories based on its function. Lastly, social distancing policies are categorised into two periods: during the COVID-19 pandemic and before/after the pandemic.

**Table 1.** Summary of literature review

| | Predictor Variable | | Previous research | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Notation** | **Description** | Huang et al. (2008) | Chung et al. (2023) | Hashimoto et al. (2016) | Kaygisiz et al. (2017) | Huang et al. (2018) | Saadat et al. (2019) | Pljakić et al. (2022) |
| Day of week | Dw 1 | Weekday | √ | - | - | - | - | - | - |
| | Dw 2 | Weekend | √ | - | - | - | - | - | - |
| Time of day | Td 1 | Morning peak hour (05.30 – 09.00 AM) | √ | - | - | - | - | - | - |
| | Td 2 | Afternoon peak hour (05.00 – 08.00 PM) | √ | - | - | - | - | - | - |
| | Td 3 | Non-peak hour | √ | - | - | - | - | - | - |
| Weather condition | Wc 1 | Good weather | √ | - | - | - | - | - | - |
| | Wc 2 | Bad weather | √ | - | - | - | - | - | - |
| Road function | Rf 1 | Toll road | - | - | √ | - | - | √ | - |
| | Rf 2 | Arterial road | - | - | √ | - | √ | √ | - |
| | Rf 3 | Collector road | - | - | - | - | √ | - | - |
| | Rf 4 | Local road | - | - | - | - | √ | - | √ |
| Road class | Rc 1 | Primary road | - | - | - | - | - | - | √ |
| | Rc 2 | Secondary road | - | - | - | - | - | - | √ |
| | Rc 3 | Tertiary road | - | - | - | - | - | - | - |
| Road type | Rt 1 | 1/1 (1 lane/1 way) | - | - | - | - | - | - | - |
| | Rt 2 | 2/1 (2 lane/1 way) | - | - | - | √ | - | - | - |
| | Rt 3 | 2/2 TB (2 lane/2 way with no median barriers) | - | - | - | √ | - | - | - |
| | Rt 4 | 3/1 (3 Lane/1 Way) | - | - | - | √ | √ | - | - |
| | Rt 5 | 4/1 (4 Lane/1 way) | - | - | - | √ | √ | - | - |
| | Rt 6 | 4/2 B (4 lane/2 way with median barriers) | - | - | - | √ | √ | - | - |
| | Rt 7 | 4/2 TB (4 lane/2 way with no median barriers) | - | - | - | √ | √ | - | - |
| | Rt 8 | 6/2 B (6 lane/2 way with median barriers) | - | - | - | √ | - | - | - |
| | Rt 9 | 6/2 TB (6 lane/2 way with no median barriers) | - | - | - | √ | - | - | - |
| | Rg 1 | Bridge | - | - | - | - | - | - | - |
| | Rg 2 | Straight | - | - | - | √ | - | - | - |

| | **Predictor Variable** | | **Previous research** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Notation** | **Description** | Huang et al. (2008) | Chung et al. (2023) | Hashimoto et al. (2016) | Kaygisiz et al. (2017) | Huang et al. (2018) | Saadat et al. (2019) | Pljakić et al. (2022) |
| Road geometry shape | Rg 3 | Multi Intersection (more than 4-Leg) | √ | - | √ | - | √ | - | √ |
| | Rg 4 | Roundabout (O) | - | - | - | - | - | - | - |
| | Rg 5 | T-intersection | √ | - | √ | - | √ | - | √ |
| | Rg 6 | Tunnel | - | - | - | - | - | - | - |
| | Rg 7 | Curve | - | - | - | √ | - | - | - |
| | Rg 8 | Misaligned quadruple intersection | √ | - | √ | - | √ | - | √ |
| | Rg 9 | Four-way intersection (X) | √ | - | √ | - | √ | - | √ |
| | Rg 10 | Y-intersection | √ | - | √ | - | √ | - | √ |
| | Rg 11 | Sharp curve | - | - | - | √ | - | - | - |
| Road width | Rw 1 | 1.5 - 3.5 m | - | - | √ | - | - | - | - |
| | Rw 2 | 4 - 6 m | - | - | √ | - | - | - | - |
| | Rw 3 | 6.5 - 8.5 m | - | - | √ | - | - | - | - |
| | Rw 4 | 9 - 11 m | - | - | √ | - | - | - | - |
| | Rw 5 | 11.5 - 13.5 m | - | - | √ | - | - | - | - |
| | Rw 6 | 14 - 16 m | - | - | - | - | - | - | - |
| | Rw 7 | 16.5 - 18.5 m | - | - | - | - | - | - | - |
| | Rw 8 | 19 - 22.5 m | - | - | - | - | - | - | - |
| | Rw 9 | >22.5 m | - | - | - | - | - | - | - |
| Land use | Lu 1 | Social and cultural | - | √ | √ | - | - | √ | - |
| | Lu 2 | Mix-use | - | - | - | √ | √ | - | - |
| | Lu 3 | Residential | - | √ | - | √ | √ | √ | - |
| | Lu 4 | Industry and warehousing | - | √ | - | √ | - | √ | - |
| | Lu 5 | Commercial and service area | - | √ | - | - | √ | √ | - |
| | Lu 6 | Government and public service area | - | - | √ | - | √ | - | - |
| | Lu 7 | Transportation | - | - | - | - | - | √ | - |
| | Lu 8 | Green open space | - | √ | - | - | - | - | - |
| Social distancing policies | Sd 1 | During Covid-19 period | - | - | - | - | - | - | - |
| | Sd 2 | Before and after the Covid-19 period | - | - | - | - | - | - | - |

## Methods and Data

This research aims to identify and analyse the environmental factors contributing to major accidents that may result in fatalities or serious injuries in Jakarta. This research focuses on exploring and identifying the environmental factors, such as road design, weather, and surrounding infrastructure, which may contribute to increased traffic accident severity leading to fatalities or serious injuries. The analytical method employed in this study is Binary Logistic

Regression, a statistical technique used to analyse the relationship between a dichotomous dependent variable and one or more independent variables. The Binary Logistic Regression method was selected because regressive logistic models are effective for analysing dependent binary outcomes by conditioning on preceding observations, improving the estimation of regression coefficients compared to ordinary logistic regression models (Bonney, 1987; Brooks and Bonney, 1989; FitzGerald and Knuiman, 1998).

The data utilised in this study are secondary in nature, obtained through official requests and collaboration with various government agencies, including the local police department and city planning agencies relevant to the objectives of the research conducted in Jakarta City. The collected data cover several key aspects to be analysed, including traffic accidents, road design, and land use data. The uniformity and validity of the data are ensured through standardised data collection methods applied by the respective agencies. After undergoing data cleaning and aggregation processes, a total of 19,415 traffic accident cases occurring across 4,654 road segments in Jakarta during the period from January 2019 to June 2023 were identified. Table 2 provides a detailed overview of the distribution of the available data in this study. The table includes a visual representation of the observed variables, making it easier to conduct further analysis on the emerging patterns. Several of the variables obtained in this study were transformed into dummy variables. Dummy variables can effectively analyse variance and covariance to compare relationships among groups. They perform comparably to standard techniques and can test differences between regression lines due to slope coefficients or intercept terms (Shih and Shih, 1978).

The analysis also employed a stepwise regression method, which involves systematically adding or removing variables to identify the most relevant predictors. This iterative process facilitates the estimation of dependency structures among variables by evaluating their significance and contribution to the model (Johnsson, 1992; Shacham and Brauner, 2014). By refining the selection of variables, stepwise regression enhances the accuracy and interpretability of the results, ensuring that the final model includes only those predictors that are most influential in explaining the dependent variable.

**Table 2.** Details of key variables selected (N = 4,654)

| | **Interpretation of variables** | **Mean** | **Std. Deviation** |
|---|---|---|---|
| Day of week | 1 if weekdays = yes, 0 otherwise | 0.84 | 0.363 |
| | 1 if weekend = yes, 0 otherwise | 0.48 | 0.500 |
| Time of day | 1 if morning peak hour (05.30 – 09.00 am) = yes, 0 otherwise | 0.35 | 0.478 |
| | 1 if afternoon peak hour (05.00 – 08.00 pm) = yes, 0 otherwise | 0.29 | 0.452 |
| | 1 if non-peak hour = yes, 0 otherwise | 0.82 | 0.383 |
| Weather condition | 1 if good weather = yes, 0 otherwise | 0.98 | 0.123 |
| | 1 if bad weather = yes, 0 otherwise | 0.09 | 0.291 |
| Road function | 1 if toll road = yes, 0 otherwise | 0.01 | 0.115 |
| | 1 if arterial road = yes, 0 otherwise | 0.21 | 0.410 |
| | 1 if collector road = yes, 0 otherwise | 0.34 | 0.474 |
| | 1 if local road = yes, 0 otherwise | 0.43 | 0.495 |
| Road class | 1 if primary road = yes, 0 otherwise | 0.08 | 0.274 |
| | 1 if secondary road = yes, 0 otherwise | 0.37 | 0.482 |
| | 1 if tertiary road = yes, 0 otherwise | 0.55 | 0.497 |
| Road type | 1 if 1/1 (1 lane/1 way) = yes, 0 otherwise | 0.04 | 0.192 |
| | 1 if 2/1 (2 lane/1 way) = yes, 0 otherwise | 0.32 | 0.466 |
| | 1 if 2/2 tb (2 lane/2 way with no median barriers) = yes, 0 otherwise | 0.61 | 0.488 |

| | Interpretation of variables | Mean | Std. Deviation |
|---|---|---|---|
| | 1 if 3/1 (3 lane/1 way) = yes, 0 otherwise | 0.15 | 0.356 |
| | 1 if 4/1 (4 lane/1 way) = yes, 0 otherwise | 0.09 | 0.288 |
| | 1 if 4/2 b (4 lane/2 way with median barriers) = yes, 0 otherwise | 0.25 | 0.430 |
| | 1 if 4/2 tb (4 lane/2 way with no median barriers) = yes, 0 otherwise | 0.04 | 0.190 |
| | 1 if 6/2 b (6 lane/2 way with median barriers) = yes, 0 otherwise | 0.10 | 0.295 |
| | 1 if 6/2 tb (6 lane/2 way with no median barriers) = yes, 0 otherwise | 0.00 | 0.065 |
| Road geometry shape | 1 if bridge = yes, 0 otherwise | 0.27 | 0.442 |
| | 1 if straight = yes, 0 otherwise | 0.89 | 0.310 |
| | 1 if multi-intersection (more than 4-leg) = yes, 0 otherwise | 0.01 | 0.115 |
| | 1 if roundabout (O) = yes, 0 otherwise | 0.02 | 0.123 |
| | 1 if T-intersection = yes, 0 otherwise | 0.13 | 0.334 |
| | 1 if tunnel = yes, 0 otherwise | 0.02 | 0.125 |
| | 1 if curve = yes, 0 otherwise | 0.08 | 0.273 |
| | 1 if misaligned quadruple intersection = yes, 0 otherwise | 0.02 | 0.128 |
| | 1 if four-way intersection (X) = yes, 0 otherwise | 0.12 | 0.320 |
| | 1 if Y-intersection = yes, 0 otherwise | 0.04 | 0.186 |
| | 1 if sharp curve = yes, 0 otherwise | 0.00 | 0.062 |
| Road width | 1 if 1.5 - 3.5 m = yes, 0 otherwise | 0.06 | 0.242 |
| | 1 if 4 - 6 m = yes, 0 otherwise | 0.34 | 0.473 |
| | 1 if 6.5 - 8.5 m = yes, 0 otherwise | 0.31 | 0.461 |
| | 1 if 9 - 11 m = yes, 0 otherwise | 0.18 | 0.381 |
| | 1 if 11.5 - 13.5 m = yes, 0 otherwise | 0.08 | 0.268 |
| | 1 if 14 - 16 m = yes, 0 otherwise | 0.02 | 0.151 |
| | 1 if 16.5 - 18.5 m = yes, 0 otherwise | 0.01 | 0.100 |
| | 1 if 19 - 22.5 m = yes, 0 otherwise | 0.005 | 0.067 |
| | 1 if >22.5 m = yes, 0 otherwise | 0.001 | 0.033 |
| Percentage of Land Use | social and cultural | 5.62 | 6.66 |
| | mix-use | 2.92 | 7.05 |
| | residential | 41.31 | 28.41 |
| | industry and warehousing | 5.23 | 13.68 |
| | commercial and service area | 22.67 | 20.05 |
| | government and public service area | 2.76 | 7.05 |
| | transportation | 1.59 | 4.65 |
| | green open space | 4.60 | 7.72 |
| Social distancing policies | 1 if during Covid-19 period = yes, 0 otherwise | 0.61 | 0.488 |

## Results and Discussion

The estimation results presented in Table 3 demonstrate a significant relationship between the independent variables, which encompass various environmental factors: (1) day of the week, (2) time of day, (3) weather conditions, (4) road function, (5) road class, (6) road type, (7) road geometry, (8) road width, (9) land use, and (10) social distancing policies, and the dependent variable, which is the occurrence of major accidents that may result in fatalities or serious injuries.

**Table 3.** Model estimation results

| Estimated Parameter | Coef. | Std.Err. | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -2.519** | 0.103 | -24.532 | 0.000 | -2.720 | -2.318 |

| **Estimated Parameter** | | | **Coef.** | **Std.Err.** | **z** | **P>\|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|---|---|
| Day of week | Weekend | | 0.537** | 0.075 | 7.185 | 0.000 | 0.390 | 0.683 |
| Time of day | morning peak hour (05.30 – 09.00 am) | | 0.382** | 0.079 | 4.854 | 0.000 | 0.228 | 0.536 |
| | afternoon peak hour (05.00 – 08.00 pm) | | 0.263** | 0.083 | 3.165 | 0.002 | 0.100 | 0.425 |
| Weather condition | bad weather | | 0.456** | 0.133 | 3.435 | 0.001 | 0.196 | 0.717 |
| Road function | toll road | | 1.412** | 0.356 | 3.962 | 0.000 | 0.714 | 2.110 |
| | arterial road | | 0.523** | 0.118 | 4.426 | 0.000 | 0.291 | 0.754 |
| | collector road | | 0.222** | 0.085 | 2.620 | 0.009 | 0.056 | 0.388 |
| Road class | road class II | | 0.370** | 0.076 | 4.868 | 0.000 | 0.221 | 0.518 |
| Road type | 2 lane/1 way | | 0.651** | 0.087 | 7.514 | 0.000 | 0.481 | 0.821 |
| | 2 lane/2 way with no median barriers | | 0.542** | 0.093 | 5.850 | 0.000 | 0.361 | 0.724 |
| | 3 Lane/1 Way | | 0.640** | 0.119 | 5.387 | 0.000 | 0.407 | 0.873 |
| | 4 Lane/1 Way | | 0.751** | 0.157 | 4.780 | 0.000 | 0.443 | 1.059 |
| | 4 lane/2 way with median barriers | | 0.389** | 0.098 | 3.972 | 0.000 | 0.197 | 0.581 |
| | 4 lane/2 way with no median barriers | | 0.595** | 0.204 | 2.910 | 0.004 | 0.194 | 0.995 |
| | 6 lane/2 way with median barriers | | 0.520** | 0.148 | 3.515 | 0.000 | 0.230 | 0.811 |
| Road geometry shape | T-intersection | | 0.482** | 0.109 | 4.436 | 0.000 | 0.269 | 0.695 |
| | Curve | | 0.325** | 0.137 | 2.381 | 0.017 | 0.057 | 0.593 |
| | Misaligned quadruple intersection | | 0.565* | 0.320 | 1.765 | 0.078 | -0.062 | 1.192 |
| | Four-way intersection (X) | | 0.236* | 0.120 | 1.959 | 0.050 | 0.000 | 0.472 |
| Road width | 6.5 - 8.5 m | | 0.313** | 0.077 | 4.062 | 0.000 | 0.162 | 0.464 |
| Percentage of Land Use | Industry and warehousing | | 0.006** | 0.003 | 2.192 | 0.028 | 0.001 | 0.010 |
| | Government and public service area | | -0.010* | 0.005 | -1.811 | 0.070 | -0.020 | 0.001 |
| Pseudo R-squ | 0.2038 | AIC | | 4918.293 | | | | |
| Log-Likelihood | -2436.1 | BIC | | 5066.539 | | | | |
| LL-Null | -3059.8 | | | | | | | |

**Notes:** Variables significant at 90% confidence level (*) and 95% confidence level (**)

## *Day of Week*

The analysis results indicate that weekends positively influence the occurrence of major accidents, which may result in fatalities, with a coefficient of 0.537. This phenomenon can be explained by the fact that weekends are often associated with riskier driving behaviour. During weekends, drivers tend to drive faster and with less caution, particularly due to lower traffic volumes and reduced police supervision (Tamakloe et al., 2021). This increases the likelihood of fatal accidents, as drivers may feel freer to drive without adhering to the necessary safety protocols.

### *Time of Day*

The analysis results indicate that time of day significantly impacts the occurrence of major traffic accidents, which can lead to fatalities. Specifically, morning peak hours (05:30-09:00) and evening peak hours (17:00-20:00) exhibit a positive relationship with major accidents, with coefficients of 0.382 and 0.263, respectively. This finding is supported by a study conducted by Adeyemi et al. (2021), where, from seven studies included in the meta-analysis, the effective sample size was 220,471. The peak hours are associated with a 41% increase in the risk of fatal injuries from accidents. Specifically, the morning and evening peak periods are associated with a 40% and 27% increase in the risk of accident-related injuries.

In contrast to the findings of this study, Huang et al. (2008) reported that traffic accidents occurring during peak hours decrease the likelihood of major accidents by as much as 60%. This phenomenon can be attributed to the high traffic volume and reduced vehicle speeds typically observed during peak hours. The increased density of vehicles on the road acts as a natural speed limiter, making high-speed collisions less likely.

### *Weather Conditions*

Weather conditions play a critical role in influencing traffic accidents, particularly during adverse weather, which can significantly impact the likelihood of major accidents. The analysis reveals that bad weather conditions are associated with a substantial increase in the occurrence of major accidents, as indicated by a coefficient of 0.456. This finding highlights the elevated risk of fatalities under such conditions, which can be attributed to factors like reduced visibility, slippery road surfaces, and impaired vehicle handling (Ashley et al., 2015; Li et al., 2019). Adverse weather not only challenges drivers' ability to maintain control of their vehicles but also increases braking distances, thereby heightening the probability of major collisions.

### *Road Function*

Road function is categorised into four types: toll roads, arterial roads, collector roads, and local roads. The analysis indicates that toll roads, arterial roads, and collector roads are significantly associated with the occurrence of major traffic accidents, with coefficients of 1.412, 0.523, and 0.222, respectively. Toll roads, with the highest coefficient, demonstrate the strongest relationship with the occurrence of major accidents. This is likely due to higher vehicle speeds and the complexity of driving conditions caused by the diversity of vehicle types using toll roads, such as cars, buses, trucks, and others. Similarly, arterial roads, which serve as primary routes connecting major urban areas, exhibit a substantial influence on major accidents, reflecting higher traffic volumes and increased exposure to risk. Collector roads, though less impactful compared to toll and arterial roads, still show a significant positive association, highlighting their role in linking smaller roads to larger networks.

### *Road Class*

Road classification refers to a system that determines the maximum vehicle load allowed on a particular road. Based on the analysis, secondary roads positively influence the occurrence of major accidents, with a coefficient of 0.370. This finding indicates that vehicles travelling on roads of this class have the potential to increase the risk of more severe accidents. This can be attributed to the road's capacity, which is frequently utilised by heavy vehicles, such as large trucks, contributing to higher kinetic energy during collisions.

## *Road Type*

Roads with one-way traffic flow are associated with major accidents that can lead to fatalities. Table 3 shows that four-lane one-way roads have the highest coefficient (0.751, $p < 0.05$), indicating that high-speed roads designed for one-directional flow can lead to major crashes due to increased vehicular speed. While one-way roads can reduce the likelihood of certain types of collisions, such as head-on and side-impact crashes between vehicles travelling in opposite directions, they may inadvertently increase the risk of major accidents (Canning et al., 1938). This is often due to higher speeds facilitated by the absence of opposing traffic, reduced driver caution, and the increased probability of high-impact collisions involving vehicles moving in the same direction.

Roads with two-way traffic flow also have a positive influence on the occurrence of major traffic accidents, although the impact is not as significant as that observed on one-way roads. Among the two-way road types, roads without median barriers exhibit the highest influence on the occurrence of major accidents. Specifically, four-lane two-way roads without median barriers demonstrate the highest coefficient (0.595), followed by two-lane two-way roads without median barriers, which show a coefficient of 0.542. These findings indicate that the absence of median barriers on two-way roads increases the likelihood of major accidents, possibly due to the higher risk of head-on collisions and reduced separation between opposing traffic flows.

In contrast, two-way roads with median barriers exhibit a different pattern. Four-lane two-way roads with median barriers have significant coefficients of 0.389, while six-lane two-way roads with median barriers show an even higher coefficient of 0.520. This indicates that, for two-way roads with median barriers, the number of lanes plays a crucial role in influencing the occurrence of major accidents. The more lanes a road has, the higher the likelihood of major accidents (Zhang et al., 2022). This could be attributed to increased vehicular speeds and the complexity of traffic manoeuvres, even with the added safety provided by the median barriers.

## *Road Geometry*

The geometry of a road refers to its physical form and structural configuration, encompassing elements such as straight segments, curves, Y-intersections, T-intersections, and various other layouts. The analysis results reveal that T-intersections (coefficient = 0.482, $p < 0.05$) and curves (coefficient = 0.325, $p < 0.05$) are positively associated with the occurrence of major traffic accidents, indicating that these road geometry types significantly contribute to an increased likelihood of severe accidents. Additionally, misaligned quadruple intersections exhibit a marginally significant impact on the occurrence of major accidents (coefficient = 0.565, $p < 0.1$), suggesting that their irregular design may pose risks to road users. In contrast, four-way intersections (X-intersection) display a smaller but still significant positive association with the occurrence of major accidents, as evidenced by a coefficient of 0.236 ($p < 0.05$). The occurrence of major traffic accidents, whether at intersections or curves, is influenced by various interrelated factors, including traffic conditions, intersection types, and driver behaviour (Wang et al., 2020).

## *Road Width*

Road width is a crucial factor influencing traffic accidents (Hashimoto et al., 2016; Sari et al., 2024). The analysis results reveal that roads with a width of 6.5-8.5 metres significantly impact the occurrence of major traffic accidents, potentially leading to fatalities. This is evidenced by a coefficient value of 0.313, indicating a positive association between road width in this range and the risk of fatal accidents.

*Land Use*

The land uses identified in this study are categorised into eight types: (1) social and cultural areas, (2) mixed-use areas, (3) residential areas, (4) industrial and warehousing areas, (5) commercial and service areas, (6) government and public service areas, (7) transportation zones, and (8) green open spaces. The analysis revealed that two of these land use types have a significant impact on the occurrence of major traffic accidents, which can lead to fatalities. Specifically, industrial and warehousing areas demonstrated a positive and significant influence on the occurrence of major accidents, with a coefficient of 0.006. This finding suggests that industrial and warehousing areas, which often experience high levels of heavy vehicle traffic, contribute to an increased risk of fatal traffic accidents. However, research conducted by Kaygisiz et al. (2017) revealed that industrial and warehousing zones do not have a significant impact on traffic accidents. This result highlights the presence of complexities that may arise from variations in urban characteristics, vehicle movement patterns, traffic density levels, and other unobserved factors in this study.

A noteworthy finding is observed in the government and public service areas, which exhibit a negative influence on the occurrence of major traffic accidents, as indicated by a coefficient of -0.010. This suggests that these areas may contribute to mitigating the occurrence of major traffic incidents. The negative relationship could be attributed to factors such as lower traffic speeds, higher levels of traffic control measures, or increased pedestrian-friendly infrastructure commonly found in government and public service zones.

## Conclusions

This study set out to examine the impact of environmental factors on major road accidents in Jakarta, focusing on incidents that result in serious injuries or fatalities. By employing a binary logistic regression model and analysing data from over 19,000 accidents across 4,654 road segments between 2019 and 2023, this research identified key predictors of accident severity, including road design, land use, weather conditions, and temporal patterns. The findings underscore the significant role of environmental factors in shaping road safety outcomes, highlighting the need to move beyond conventional approaches that primarily attribute accidents to human error.

The results reveal that weekends, peak traffic hours, adverse weather conditions, and specific road types—such as one-way four-lane roads—significantly increase the likelihood of major accidents. Additionally, industrial and warehousing areas emerge as high-risk zones, while government and public service zones are associated with lower accident risks. These insights demonstrate that accident severity is not merely a function of driver behaviour but is also deeply influenced by the built environment and external conditions.

From a policy and urban planning perspective, this study provides actionable recommendations for reducing major traffic accidents. Prioritising safety-oriented road design improvements, such as installing median barriers, optimising intersections, and enhancing pedestrian infrastructure, can mitigate accident risks. Land use planning must also be better integrated into road safety strategies, particularly in high-risk industrial zones where heavy vehicle movement contributes to accident severity. Additionally, adaptive traffic management measures—such as real-time monitoring, enhanced drainage systems for flood-prone areas, and stricter enforcement during high-risk periods—can help reduce fatalities and severe injuries.

Beyond Jakarta, these findings offer valuable lessons for other rapidly urbanising cities, particularly in developing regions where similar transport and infrastructure challenges persist.

Many cities across Southeast Asia, South Asia, Latin America, and Africa experience high traffic congestion, mixed land-use patterns, and limited enforcement of traffic regulations. This study highlights replicable strategies that cities can adopt to enhance road safety, including data-driven accident analysis, evidence-based policymaking, and infrastructure upgrades tailored to local risk factors. The results emphasise the importance of integrating environmental considerations into urban mobility planning, rather than treating road safety as an issue of driver behaviour alone.

Despite its contributions, this study has limitations. The reliance on secondary data means that certain variables, such as real-time driver behaviour and vehicle conditions at the time of the accident, could not be fully accounted for. Additionally, while Jakarta provides a representative case for rapidly urbanising cities, the findings may not be directly transferable to urban contexts with different socio-economic and infrastructural conditions. Future research should incorporate on-site accident investigations, real-time traffic monitoring, and comparative studies across multiple cities to deepen the understanding of how environmental factors shape accident severity. Furthermore, exploring the interaction between human, vehicle, and environmental factors could offer a more holistic approach to mitigating road accidents globally.

## Declaration of Generative AI Use In Writing

During the preparation of this work, the authors used Quillbot, developed by Learneo, Inc., to assist with paraphrasing and refining the language in certain sections. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final content of the publication.

## Ethics Statement

This study did not require ethical approval as it was based solely on secondary data obtained from official government sources, including traffic accident records, road infrastructure data, and land use data, which are publicly available and anonymised. No personal or sensitive information related to individual accident victims was accessed or used in this research. The use of aggregated, non-identifiable data ensured that the study posed no risk to human participants and complied with relevant ethical standards for research involving secondary data analysis.

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